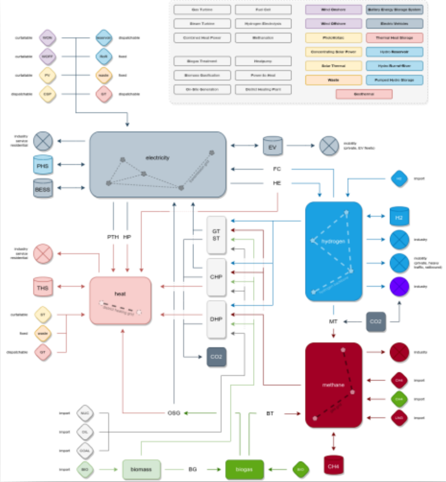
CALCULATING SCENARIO-INVARIANT OPTIMAL INVESTMENT UNDER UNCERTAINTY (USING BENDERS DECOMPOSITION)

AIT Austrian Institute of Technology GmbH

Stefan Strömer

MOTIVATION



"Based on our simplified and aggregated depiction of reality, and given the chosen assumptions and choices for all parameters, the expected total system costs – considering an equal probability for all scenarios – are approximately 15 billion EUR."

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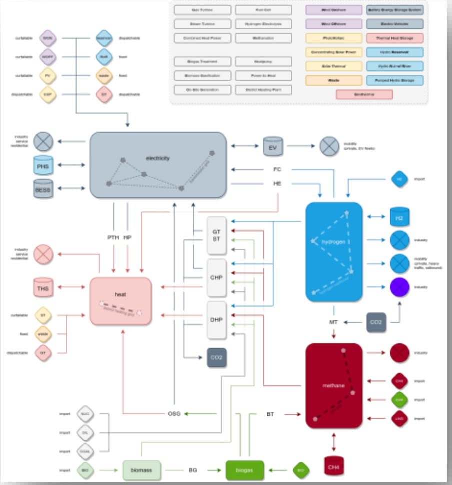

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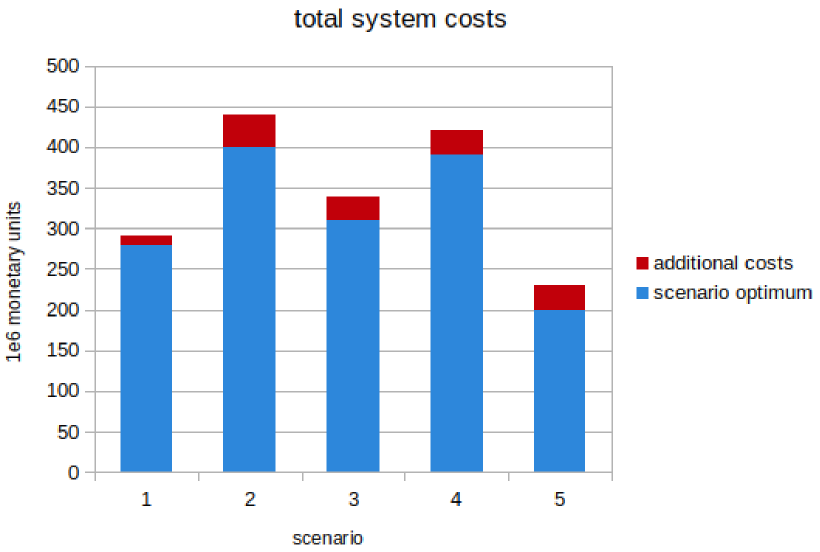
IDEA

For some "global" investment decision:



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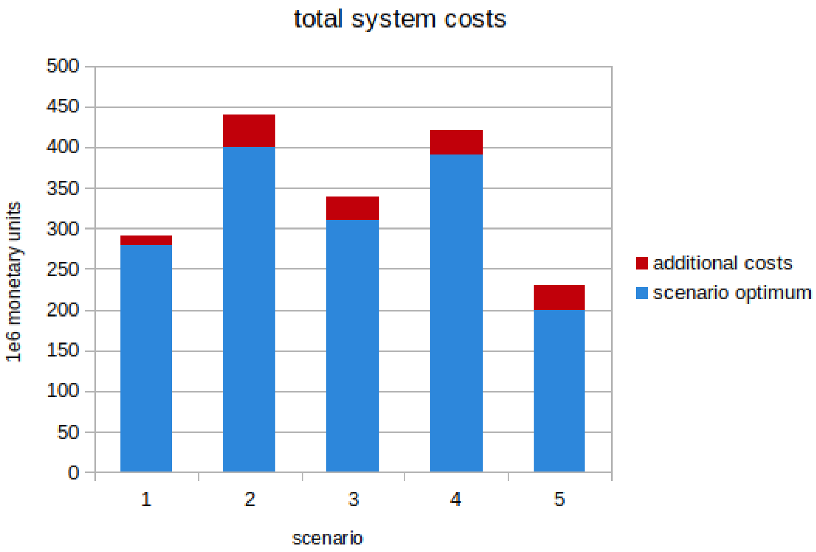
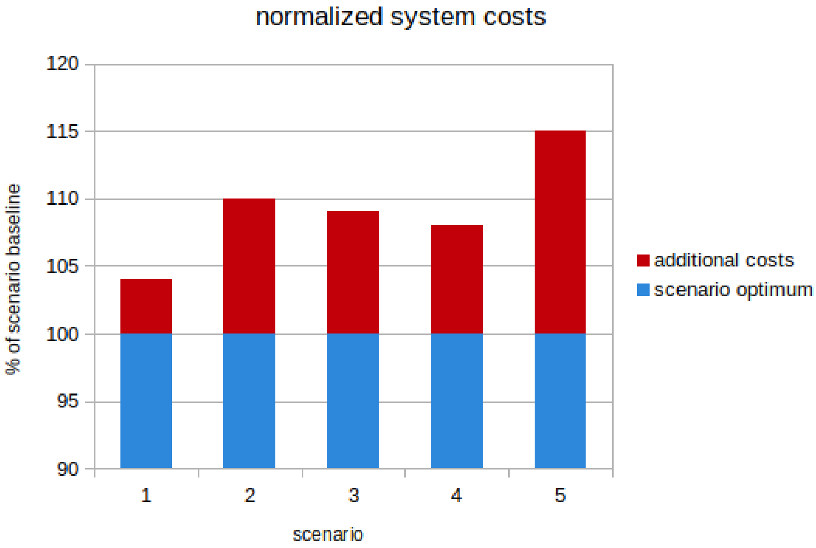
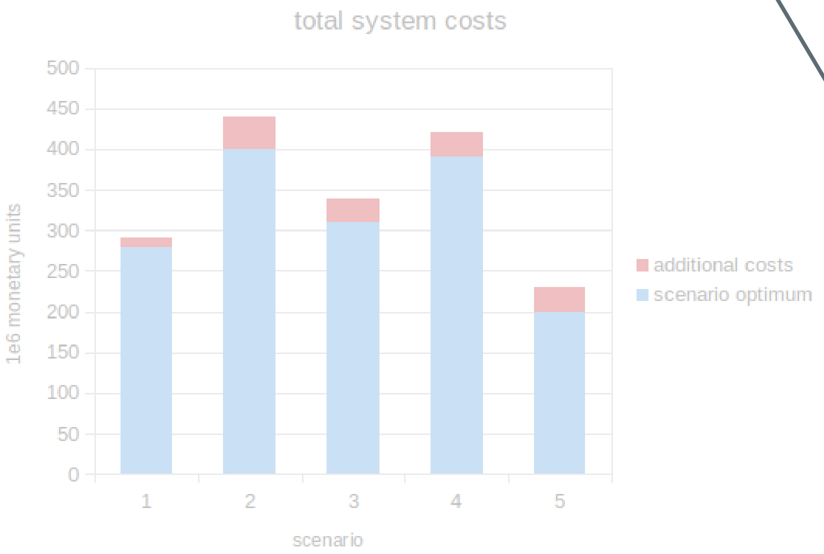
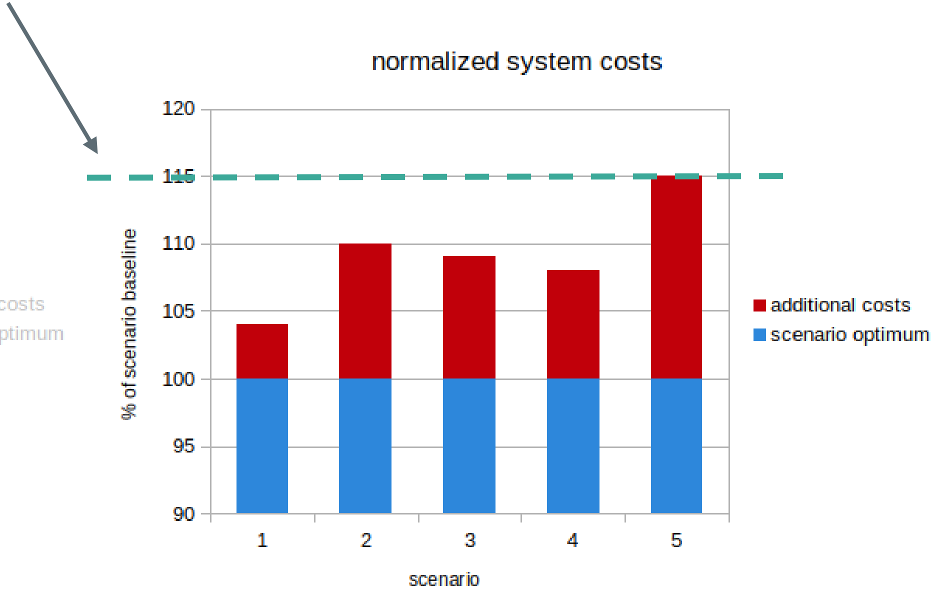




IDEA

Find an investment decision that minimizes the relative additional costs across all scenarios:





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Basis:

- standard energy system model of your choice (that can calculate duals of installed capacity)
- ensure feasibility using load shedding, …

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Combine:

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Add:

- model endogenous near-optimality
- a way to handle "worst case" scenarios (to prevent replicating robust optimization)

(RE)FORMULATION

$$\min_{y \in Y} \max \left\{ \min_{x_s \in X(y,s)} f_s(y, x_s) \cdot \underline{f_s(y_s^*, x_s^*)^{-1}} \right\}$$

single scenario optimum

(RE)FORMULATION

$$\min_{y \in Y} \max \left\{ \underbrace{\min_{x_s \in X(y,s)} f_s(y, x_s)}_{\text{optimal operation}} \cdot \underbrace{f_s(y_s^*, x_s^*)^{-1}}_{\text{single scenario optimum}} \right\}$$

(RE)FORMULATION

worst "foregone profits"

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(RE)FORMULATION

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cost-minimal overall investment

optimal operation

single scenario optimum

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$$\min_{y \in Y, z} z$$

$$s.t.$$

$$z \geq \min_{x_s \in X(y,s)} f_s(y, x_s) \cdot f_s(y_s^*, x_s^*)^{-1} \qquad \forall s \in S$$

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$$z \geq \min_{x_s\in X(y,s)} f_s(y,x_s) \cdot f_s(y_s^*,x_s^*)^{-1} - M \cdot q_s \qquad \forall s \in S$$

$$\sum_{\{s\in S\}} q_s \cdot w_s \leq 1 - q$$

IMPLEMENTATION

Fixes:

- proper scaling to prevent numerical problems due to extreme coefficients

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General:

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- sub-problems can be sped up (no crossover, higher tolerances, …)
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Specials:

- model modifications are minimal – fast solves with in-memory updates (AIT MarketFlow); keep technical differences in LHS modification in mind (e.g. Xpress vs. Gurobi)
- only objective function and proper duals are necessary for the sub-problems, which allows further decomposition with ADMM-consensus based approaches
- implicit warm-starts possible

<u>**NO RESULTS**</u> ... BUT A PICTURE

<u>Cost parameters:</u> PyPSA-Eur

<u>Installed capacities:</u> ENTSO-E

<u>Scaled timeseries data for 41 years:</u>

Grochowicz, A., van Greevenbroek, K., Benth, F. E., & Zeyringer, M. (2022). *Intersecting near-optimal spaces: European power systems with more resilience to weather variability.*

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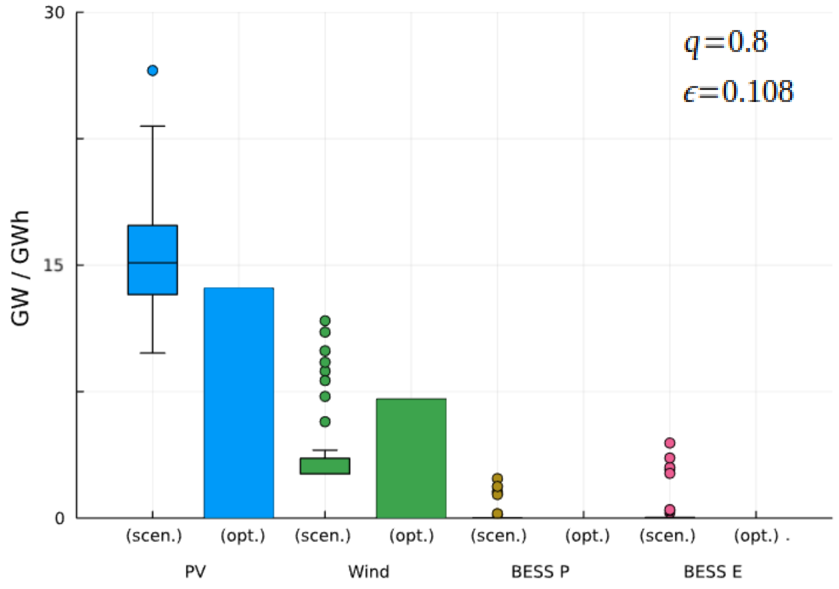

Comparison: separate scenario approach ("scen." using boxplots) and scenario-invariant approach ("opt." using barplot). BESS P / E = battery energy storage power/energy. Data using scaled historic years for 2030. Showing total installed capacity after investment in Austria.

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THANK YOU!

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